REMARKS

Applicant respectfully requests reconsideration and allowance of the subject application. Claims 8, 32, 35 and 55 are amended. New claims 57-66 are added. Claims 1-30, 32-38, 40-44 and 46-66 are pending in this application.

The amendment to the specification addresses minor informalities noted during review. No new matter is added by the amendment to the specification.

35 U.S.C. § 112

Claims 32-38, 55 and 56 stand rejected under 35 U.S.C. §112, second paragraph. Claims 32 and 55 have been amended to obviate the concerns noted in the Office Action, however, these amendments are not intended to alter the scope of the claims. Accordingly, Applicant respectfully requests that the §112 rejections be withdrawn.

Art Rejections

Claims 1, 8, 9, 32, 35-38, 40-44 and 48-51 stand rejected under 35 U.S.C. 102(b) as being anticipated by "Relevance Feedback Techniques in Interactive Content-Based Image Retrieval" by Rui et al. (Jour. Vis. Comm. and Image Rep., Vol. 10, pp. 39-62, March 1999) (hereinafter "RFT"). Claims 11-18, 46 and 47 stand rejected under 35 U.S.C. 102(a) as being anticipated by "MindReader: Querying Databases Through Multiple Examples" by Ishikawa et al. (Proc. 24th VDLB Conf. (New York), 1988, pp. 218-227) (hereinafter "MR").

Claims 10 and 52 stand rejected under 35 U.S.C. §103(a) as being unpatentable over RFT. Claims 2-7, 19-30, 33, 34 and 53-56 stand rejected under 35 U.S.C. §103(a) as being unpatentable over RFT in view of MR. Applicant respectfully traverses the anticipation and unpatentability rejections and requests reconsideration.

35 U.S.C. § 102

Anticipation is a legal term of art. Applicant notes that in order to provide a valid finding of anticipation, several conditions must be met: (i) the reference must include every element of the claim within the four corners of the reference (see MPEP §2121); (ii) the elements must be set forth as they are recited in the claim (see MPEP §2131); (iii) the teachings of the reference cannot be modified (see MPEP §706.02, stating that "No question of obviousness is present" in conjunction with anticipation); and (iv) the reference must enable the invention as recited in the claim (see MPEP §2121.01). Additionally, (v) these conditions must be simultaneously satisfied.

The §102 rejection of claims 1, 8, 9, 11-18, 32, 35-38, 40-44 and 46-51 is believed to be in error. Specifically, the PTO and Federal Circuit provide that §102 anticipation requires that each and every element of the claimed invention be disclosed in a single prior art reference. *In re Spada*, 911 F.2d 705, 15 USPQ2d 1655 (Fed. Cir. 1990). The corollary of this rule is that the absence from a cited §102 reference of any claimed element negates the anticipation. *Kloster Speedsteel AB, et al. v. Crucible, Inc., et al.*, 793 F.2d 1565, 230 USPQ 81 (Fed. Cir. 1986).

No §103 rejection has been lodged regarding claims 1, 8, 9, 11-18, 32, 35-38, 40-44 and 46-51. Accordingly, if Applicant can demonstrate that RFT does not disclose any one claimed element with respect to claims 1, 8, 9, 32, 33, 36 and 37, or that MR does not disclose any one claimed element with respect to claims 11-18, 46 and 47, the associated §102 rejection must be withdrawn, and a

subsequent non-Final action made with a different rejection in the event that the Examiner still finds such claim(s) to be not allowable.

RFT describes relevance feedback techniques in interactive content-based image retrieval (Title). RFT describes an algorithm (Calcs. 3-8) wherein a query object Q is described in terms of features F having associated presentation vectors r_{ij} (Calcs. 3-5 and associated text). The user's information need is distributed among different features f_i of the query object Q, according to their corresponding weights W_{ij}. The various objects' similarities to the query Q is calculated according to a similarity measure m_{ij} and the weights W_{ijk} (Calc. 6) and feature similarity values are calculated (Calc. 7). An overall similarity is then determined (Calc. 8), and the objects in the database are ordered by their overall similarity to Q (item 7) and then are ranked by the user as to relevancy (item 8). The system updates the weights according to the user's feedback such that the adjusted Q is a better approximation to the user's information need (item 9), and the system iterates the comparison of the adjusted Q to the objects in the database (item 10).

MR describes a method for querying databases through multiple examples (Title). MR teaches that the depends on incorporation of user feedback to calculate a symmetric distance matrix M (sec. 3.2), which represents a generalized ellipsoid distance function (Table 1, Figure 2). When an inverse to a weighed covariance matrix C exists, the matrix M that minimizes Calc. 4 is: $M = (\det(C))^{1/n}C^{-1}$ (Theorem 2, page 221, Appendix B). When M is restricted to diagonal matrices only, M has elements $m_{jj} \alpha\ 1/(\sigma_j^2)$. When the covariance matrix C is singular and non-invertible (i.e., when C^{-1} does not exist), a pseudo-inverse matrix or Moore-Penrose matrix is used (Theorem 3, Appendix D).

In contrast to RFT, claim 1 recites "One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including: receiving an initial image selection; generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection; selecting a set of potentially relevant images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images; receiving feedback regarding the relevance of one or more images of the set of potentially relevant images; generating a new plurality of query vectors based at least in part on the feedback; generating a weighting of feature elements based at least in part on the feedback; and selecting a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors", which is not taught or disclosed by RFT.

RFT does not teach or disclose any computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, cause the one or more processors to perform acts ...., as recited in claim 1. RFT is silent with respect to implementation of any of the ideas described by RFT.

In other words, RFT does not provide any description regarding implementation whatsoever. Examples of approaches that might be employed could include an ASIC or neural network or an analog computer, none of which involve computer readable media or a computer program that is executable by a processor.

RFT does not teach or disclose any computer readable media including a computer program that is executable by a processor. Put another way, MR is completely void of the language "computer readable media" or "computer program", or, for that matter, "processor". As such, RFT does not provide the elements recited in claim 1 and cannot possibly enable the recitation of claim 1.

Further, RFT teaches (p. 3, section 2) that the object O is represented as O = O(D, F, R). D, F and R correspond to predetermined quantities, respectively identified by RFT (p. 3, section 2, "The Multimedia Object Model") as follows:

- D is the raw image data, e.g., a JPEG image.
- $F = \{f_i\}$ is a set of low-level visual features associated with the image object, such as color, texture and shape.
- $R = \{r_{ij}\}$ is a set of representations for a given feature f_i ....

RFT explicitly states (p. 3, last sentence) that "a query Q has the same model as that of the image objects".

RFT explicitly teaches (p. 4, section 3) that "An image object model O, together with a set of similarity measures $M = \{m_{ij}\}$, specifies a CBIR model (D, F, R, M). The similarity measures are used to determine how similar or dissimilar two objects are." RFT also teaches (p. 4, step 2) that "The user's information need, represented by the query object Q, is distributed among different features f_i, according to their corresponding weights W_{ij}." RFT teaches (section 3.1) updating the <u>weights</u> to reflect different user emphases, stating (p. 4, step 9) that "The system updates the <u>weights</u> according to the user's feedback such that the adjusted Q is a better approximation to the user's information need."

In other words, the portion of the query Q that is modified is other than the information associated with the feature vectors f_i of the features F. As such, RFT does not teach "generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection" after receiving the query vectors, as recited in claim 1. RFT teaches that the query objects include the set of low-level features F that are characterized by the feature vectors f_i, as do the data objects. RFT does not teach or disclose modification of the properties D, F or R in response to initial image selection or subsequent thereto.

As such, RFT does not teach "generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection", as recited in claim 1.

RFT further teaches that the user feedback is solely reflected in the weights, stating (p. 3) that "The weights are essential in modeling high level concepts and perception subjectivity. Section 3 discusses how the weights are *dynamically* updated based on the relevance feedback to track user's information need." As such, RFT does not and cannot teach "generating a new plurality of query vectors based at least in part on the feedback", as recited in claim 1.

In contrast to RFT, claim 8, as amended, recites "One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including: receiving an initial image selection; generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection; selecting a set of potentially relevant

images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images; receiving feedback regarding the relevance of one or more images of the set of potentially relevant images; generating a new plurality of query vectors based at least in part on the feedback; generating a weighting of feature elements based at least in part on the feedback; and selecting a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors, wherein f_i represents a summation, over the images in the set of potentially relevant images, of a product of a relevance of the image and a distance between the query vector and the feature vector, and wherein the selecting a new set of potentially relevant images comprises combining, for each image, a weighted distance between the plurality of query vectors and the plurality of feature vectors, and wherein the weight (u_i) for each of a plurality (I) of distances between a query vector and a corresponding feature vector is calculated as:

$$u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}\text{",}$$

which is not taught or disclosed by RFT.

RFT does not teach or disclose "One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to", as recited in claim 8. RFT does not teach or disclose "generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection", as recited in claim 8. RFT also does not teach or disclose

"generating a new plurality of query vectors based at least in part on the feedback", as recited in claim 8.

In contrast to RFT, claim 48 recites "A method of generating a weight to apply to distances between query vectors and feature vectors when combining the distances, the method comprising: receiving feedback regarding the relevance of each image of a set of images; wherein f_i represents a summation, over the images in the set of images, of a product of a relevance of the image and a distance between the query vector and the feature vector; and generating a weight (u_i) for each of a plurality (I) of distances between a query vector corresponding to one of a plurality (I) of features and a feature vector corresponding to the one of the plurality (I) of features as:

$$u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}",$$

which is not taught or disclosed by RFT.

The weights u_i calculated as recited in claims 8 and 48 are a summation of square roots of summations of products of relevance and distance between the query vector and the feature vector. A square root operation is not a linear operation.

RFT explicitly discloses that the weights W_{ij} are formed using linear techniques (Calcs. 17-19), are normalized using linear operations (Calc. 20) and are modified linearly (paragraph immediately preceding Calc. 9). RFT teaches

that use of such linear techniques allows two levels of calculation to be combined into one, as represented in Calc. 9.

Claim 32 recites "A method comprising: for one of a plurality of images and each of a plurality of features, generating, based on a set of search criteria, a query vector for the feature, identifying a feature vector, corresponding to the image, for the feature, and determining how closely the feature vector matches the query vector; and determining how closely the image matches the set of search criteria based on how closely, for the plurality of features, the feature vectors match the query vectors, wherein generating the query vector comprises generating the query vector based at least in part on user relevance feedback regarding how relevant images previously displayed to a user were", which is not taught or disclosed by RFT.

RFT describes an approach whereby an object's similarity to a query object is evaluated (step 4), the representation's similarity values are combined into a feature's similarity value (weight W_{ij} for the feature, step 5) and these similarities are then combined (step 6) to provide an overall similarity. This overall similarity is then employed to evaluate rank ordering (step 7, stating that "The objects in the database are ordered by their overall similarity to Q.").

In contrast, the process recited in claim 32 reflects a hierarchical approach to determining how closely two images match. First individual distances between the feature vectors and the query vectors are determined, and then these individual distances are combined.

Further, RFT does not teach or disclose "generating the query vector based at least in part on user relevance feedback" together with "determining how

closely the feature vector matches the query vector", as recited in claim 32, because RFT teaches modification of weights for query feature vectors. The modified weights are used in comparing predetermined query feature vectors to feature vectors of the objects.

Claim 41 recites "One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including: identifying a plurality of query vectors for one image, each query vector corresponding to one of a plurality of features; identifying a plurality of feature vectors for another image, each feature vector corresponding to one of the plurality of features; for each feature, determining a distance between the corresponding query vector and the corresponding feature vector; and combining the distances to generate a value representing an overall distance between the one and the another image, wherein the identifying the plurality of query vectors comprises generating the plurality of query vectors based at least in part on user relevance feedback regarding how relevant images previously displayed to a user were", which is not taught or disclosed by RFT. As noted above, determining a distance of a feature-by-feature basis, as recited in claim 41, reflects a hierarchical approach, while RFT determines overall similarity.

Further, RFT does not teach or disclose "generating the query vector based at least in part on user relevance feedback" together with "determining how closely the feature vector matches the query vector", as recited in claim 32, because RFT teaches modification of weights for query feature vectors. The

modified weights are used in comparing predetermined query feature vectors to feature vectors of the objects.

Claim 50 recites "A system comprising: a client device; a collection of a plurality of images; an image server, coupled to the client device and the collection of a plurality of images, the image server to receive image retrieval requests from the client device and to, receive an initial image selection from the client device, generate a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection, select a set of potentially relevant images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images, receive feedback regarding the relevance of one or more images of the set of potentially relevant images, generate a new plurality of query vectors based at least in part on the feedback, generate a weighting of feature elements based at least in part on the feedback, and select a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors", which is not taught or disclosed by RFT.

As noted above with respect to claim 1, RFT does not teach or disclose "image server to ... generate a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection", as recited in claim 50. RFT instead teaches computing distances from image properties of the image model O(D, F, R). There is no teaching in RFT of extracting low-level features F. As also noted above with respect to claim 1,

RFT does not teach or disclose an image server to "generate a new plurality of query vectors based at least in part on the feedback", as recited in claim 50. RFT instead teaches modification of weights only. RFT further does not teach or disclose anything to "select a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors", as recited in claim 50. RFT teaches modification of the weights to incorporate user relevancy feedback.

Claim 51 recites "One or more computer readable media as recited in claim 1, wherein the receiving feedback comprises receiving feedback in a range including at least Highly Relevant, Relevant, No Opinion, Irrelevant, and Highly Irrelevant", which is not taught or disclosed by RFT. As noted above with respect to claim 1, RFT is void of any teaching or disclosure regarding implementation of the ideas presented in RFT.

Claim 11 recites "A method of selecting between two types of matrixes to be used to weight, based on relevance feedback, a plurality of feature elements for image retrieval, the method comprising: selecting one of the two types of matrixes based on both a number of previously retrieved relevant images and a length of a feature vector including the plurality of feature elements", which is not taught or disclosed by MR.

The Office Action states (p. 8) that MR discloses a method of selecting between two types of matrixes as claimed. See section 3 on pages 220-221 for this disclosure. Refer specifically to sections 3.2 - 3.4 and Appendix D for the details of this disclosure. In particular, MR teaches "a method of selection [See section

3.4] between two types of matrix (a full covariance matrix OR Moore-Penrose inverse matrix] to be used to weight, based on relevance feedback, a plurality of feature elements for image retrieval ...." Applicant disagrees and requests reconsideration.

MR discloses (section 3) use of a symmetric matrix M as a generalized ellipsoid distance matrix relating to distances between a query point described by a vector q and sample vectors x in a data point matrix X. MR provides no teaching or disclosure of "a plurality of feature elements for image retrieval" as recited in claim 11. MR also provides no disclosure of use of "selecting between two types of matrixes to be used to weight" such, as recited in claim 11.

MR discloses several examples: finding information relating to "mildly overweight" people (p. 219, left column, Fig. 1) based on weight divided by height in a data system characterized by weight and height coordinates (a "diagonal inquiry") and finding points near a road segment using the Mongtomery County dataset, comprising endpoints of road segments in Montgomery County, Maryland (p. 223, left hand column; Fig. 6). These are both two-dimensional datasets; neither involves images. Other areas where MR indicates the model will be useful include multimedia systems and digital libraries, general approximate matching in traditional databases, time sequences ("find stocks similar to, e.g., IBM's stock") and spatial databases ("find gas stations close to the I-270 interstate highway"). MR provides no indication of what kinds of search criteria or data would be useful in these contexts - keywords, human-defined numerical rankings.

Further, MR does not teach or disclose choosing between two types of matrixes, as recited in claim 11. MR teaches (sections 3.3 and 3.4) selection

between three types of matrixes: a full covariance matrix (theorems 1 and 2, appendix B), a diagonal matrix, or a pseudo-inverse or Moore-Penrose matrix (section 3.4, appendix C).

Claim 12 recites that "the selecting comprises selecting one of the two types of matrixes based on both a number of previously retrieved potentially relevant images which were identified by a user as being relevant, and the length of the feature vector including the plurality of feature elements", which is not taught or disclosed by MR. The Office Action cites Table I and section 3.2 with respect to claim 12. Table I is void of any reference whatsoever to any number of previously retrieved images or of potentially relevant images. Sections 3.2-3.4 do not cure these deficiencies.

Claim 13 recites that "the plurality of feature elements are all elements of the same feature". The sample vectors x described by MR may be, for example, height and weight data for an individual - different features of the same subject or element, and not "elements of the same feature" as recited in claim 13.

In contrast to MR, claim 14 recites that "the selecting comprises using a first type of matrix if the number of retrieved relevant images is less than the length of the feature vector, and otherwise using a second type of matrix", while claim 15 recites that "the first type of matrix comprises a diagonal matrix and wherein the second type of matrix comprises a full matrix", which aspects are not taught or disclosed by MR.

MR discloses that when the covariance matrix inverse C^{-1} exists, either a matrix $M = (\det(C))^{1/n}C^{-1}$ minimizes Calc. 4 or, if the matrix M is restricted to being diagonal, Calc. 9 (M has elements $m_{jj} \alpha\ 1/(\sigma_j^2)$) minimizes Calc. 4 (theorem

2). MR discloses that when the number of feedback points is less than the number of feature dimensions, the Moore-Penrose inverse matrix satisfies Calc. 4. MR teaches use of either a full or diagonal matrix OR the use of the Moore-Penrose matrix and does not provide any selection criteria for when to discriminate between the first two options.

In contrast to MR, claim 16 recites that "the selecting comprises using a first type of matrix if the length of the feature vector exceeds the number of retrieved relevant images by at least a threshold amount, and otherwise using a second type of matrix", which is not taught or disclosed by MR.

The Office Action states that MR discloses the subject matter recited in claim 16 when the threshold amount is chosen to be one. Applicant disagrees. MR does not teach or describe choosing between two types of matrixes or doing so based on feature vector length or any number of previously retrieved images.

Further, using MR's notation, claim 16 recites that $n > N +$ threshold corresponds to the first type of matrix. The second matrix type would be used when $n < N +$ threshold.

MR, in contrast, teaches that the singular covariance matrix case arises when the number of feedback points N is less than the number of feature dimensions n, i.e., $N < n$ and teaches use of either one of two other types of matrixes (Calcs. 6 and 7, or Calc. 8) otherwise, that is, when $N \geq n$. Such does not correspond to use of any threshold in addition to a number of datapoints in making any decision.

Claim 17 depends from claim 16 and recites that "the first type of matrix comprises a full matrix and the second type of matrix comprises a diagonal

matrix", which is not taught or disclosed by MR. As noted above, MR fails to teach or disclose the subject matter recited in claim 16. As also noted above, MR fails to teach or disclose choosing between diagonal or full matrices based on a number of prior samples.

Claim 18 recites "One or more computer readable media including a computer program that is executable by a processor to perform the method recited in claim 11", which is not taught or disclosed by MR. MR is completely silent as to how the ideas described by MR might be implemented and does not provide any description regarding implementation whatsoever. Examples of approaches that might be employed could include an ASIC or neural network or an analog computer, none of which represent computer readable media or a computer program that is executable by a processor.

In other words, MR does not teach or disclose any computer readable media including a computer program that is executable by a processor. Put another way, MR is completely void of the language "computer readable media" or "computer program".

In contrast to MR, claim 46 recites "A method of generating a query vector to compare to a feature vector of another image, the method comprising: receiving feedback regarding the relevance of each image of a set of images; wherein N represents the number of images in the set of images for which user relevance feedback has been received, π_n represents the relevance of image n in the set of images, $\vec{\pi}^T$ represents a transposition of a vector generated by concatenating the individual π_n values, and X represents an image matrix that is generated by stacking N training vectors corresponding to the set of images into a matrix; and

generating a query vector ($\vec{q}$) corresponding to one of a plurality of features as follows:

$$\vec{q} = \frac{\vec{\pi}^T X}{\sum_{n=1}^{N} \pi_n} \text{"},$$

which is not taught or disclosed by MR.

MR teaches (with respect to theorem 1) that a query vector = X^T(goodness values)/(sum of goodness values), where X represents the entire data point matrix (see Table I). This is not the same as the recitation of claim 46, which provides that the query vector is given as the transpose of a vector formed by concatenating relevance values times an image matrix formed by stacking N training vectors all divided by a sum of the relevance values.

Further, there is no teaching or disclosure in MR of searching images, or of "receiving feedback regarding the relevance of each image of a set of images", as recited in claim 46.

Dependent claims 9, 12-18, 35-38, 40, 42-44, 47, 49 and 51 are allowable as depending from an allowable base claim and for their own recited features which are neither shown nor suggested by the prior art.

RFT fails to provide the elements recited in Applicants' claims 1, 8, 9, 32, 35-38, 40-44 and 48-51, and MR fails to provide the elements recited in claims 11-18, 46 and 47, as required by MPEP §2121, see item (i) above in "Anticipation is a legal term of art". As a result, neither RFT nor MR can set forth these respective elements as they are recited in the respective claims, as required by MPEP §2131 (item (ii), supra). Accordingly, the teachings of the references must be modified in order to arrive at the subject matter of the claims, in contravention of MPEP

§706.02 (item (iii), supra). Additionally, because neither RFT nor MR meets the criteria for a finding of anticipation outlined above, neither RFT nor MR cannot enable the subject matter recited in the respective claims, and thus the references and the arguments in the Office Action fail to meet the criteria of MPEP §2121.01 (item (iv), supra). Inasmuch as none of the requirements for a finding of anticipation are met by the arguments presented and the references, the anticipation rejections of claims 1, 8, 9, 11-18, 32, 35-38, 40-44 and 46-51 are defective and should be withdrawn, and claims 1, 8, 9, 11-18, 32, 35-38, 40-44 and 46-51 should be allowed.

35 U.S.C. § 103

In contrast to RFT, claim 10 recites "One or more computer readable media as recited in claim 1, wherein the low-level features include: a color moments feature, a wavelet based texture feature, and a water-fill edge feature", which is not taught, disclosed, suggested or motivated by RFT. As noted above with respect to claim 1, RFT is silent with respect to computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to ...." RFT is silent with respect to implementation. RFT is also silent with respect to any "water-fill edge feature", as recited in claim 10. The discussion of Calcs. 1 and 2, cited in the Office Action (p. 10) is devoid of any mention of "a wavelet based texture feature".

The Office Action states (p. 10) that the Examiner takes Official Notice that such representations were of common practice. Additionally, the Office Action admits, on the record, that the reference fails to supply all aspects of the subject matter as recited in the claim.

Specifically, the Office Action admits (p. 10) that RFT fails to disclose "that the texture feature includes "a wavelet-based texture feature" and that the shape feature includes "a water-fill edge feature" as claimed" and then states that "However, this is only because RFT is silent on specific examples for representations of texture and shape within this particular article." Applicant notes that RFT provides numerous specific examples (see, e.g., Calc. 23 and text associated therewith, listing color histogram, color moments, Tamura, co-occurrence matrix, Fourier descriptor, chamfer shape descriptor; see also list of texture feature representations on the second page of the article).

The Office Action further states (p. 10, bottom, continuing on p. 11) that "The examiner takes Official notice that wavelet based texture features were texture representations of common practice in the art at the time the invention was made, and further that water-fill edge features were shape representations of common practice in the art at the time the invention was made."

Claim 52 recites "One or more computer readable media as recited in claim 1, wherein the receiving feedback comprises receiving feedback via speech recognition", which is not taught, disclosed, suggested or motivated by RFT.

The Office Action states (p. 11) that "RFT does not explicitly disclose that the receiving feedback comprises speech recognition as claimed. This however, is only because RFT is silent on the computerized means for specifying the user feedback. The examiner takes Official notice that the use of speech recognition for user input/feedback was common practice ...."

With respect to both claims 10 and 52, inasmuch as these allegations are not supported by the reference, they must be based on either (i) personal knowledge of the Examiner or (ii) hindsight reconstruction based on Applicants' own disclosure, employing an "obvious to try" standard of unpatentability. Either is improper as is discussed in further detail below.

Applicant notes the requirements of MPEP §707, entitled "Examiner's Letter or Action". This MPEP section states, in subsection (d)(2), that: "When a rejection in an application is based on facts within the personal knowledge of an employee of the Office, the data shall be as specific as possible, and <u>the reference must be supported, when called for by the applicant, by the affidavit of such employee</u>, and such affidavit shall be subject to contradiction or explanation by

the affidavits of the applicant and other persons." Accordingly, Applicant calls for such affidavit in the event that the Examiner persists with the rejection of claims 10 and 52 based on the personal knowledge of the Examiner.

As there is no basis for the Examiner's contentions within the cited references, the only possible motivation for these contentions is hindsight reconstruction wherein the Examiner is utilizing Applicant's own disclosure to construct a reason for modifying and adding to the disclosure of the cited reference. The Examiner is reminded that hindsight reconstruction is not an appropriate basis for a §103 rejection. (See, e.g., *Interconnect Planning Corp. v. Feil*, 227 USPQ 543, 551 (Fed. Cir. 1985); *In re Mills*, 16 USPQ2d 1430 (Fed. Cir. 1990) (explaining that hindsight reconstruction is an improper basis for rejection of a claim).)

Further, suggestion to modify as put forth in the Office Action appears to employ an improper "obvious to try" rationale, as is discussed below in more detail with reference to MPEP §2145(X)(B). This MPEP section states that:

> The admonition that 'obvious to try' is not the standard under §103 has been directed mainly at two kinds of error. In some cases, what would have been 'obvious to try' would have been to vary all parameters or <u>try each of numerous possible choices</u> until one possibly arrived at a successful result, where the prior art gave either no indication of which parameters were critical or <u>no direction as to which of many possible choices is likely to be successful</u>.... In others, what was 'obvious to try' was to explore a new technology or general approach that seemed to be a promising field of experimentation, where the prior art gave only general guidance as to the particular form of the claimed invention or how to achieve it. *In re O'Farrell*, 853 F.2d 894, 903, 7 USPQ2d 1673, 1681 (Fed. Cir. 1988) (citations omitted).

No guidance has been identified within the reference to determine which elements to pick or choose from the reference, or of how to couple them to somehow arrive at subject matter such as is claimed (see also discussion of MPEP §2143 infra).

Additionally, the admissions, on the record, that the reference fails to teach, disclose, suggest or motivate the subject matter recited in claims 10 and 52, show that a prima facie case of unpatentability has not been established (see discussion of MPEP §2143 below).

In contrast to RFT, claim 2 recites "One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including: receiving an initial image selection; generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection; selecting a set of potentially relevant images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images; receiving feedback regarding the relevance of one or more images of the set of potentially relevant images; generating a new plurality of query vectors based at least in part on the feedback; generating a weighting of feature elements based at least in part on the feedback; and selecting a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors, wherein the selecting a new set of potentially relevant images comprises using a matrix in determining the distance between one of the new plurality of query

vectors and one of the plurality of feature vectors, and further comprising dynamically selecting the matrix based on both a number of images in the set of potentially relevant images for which relevance feedback was input and a number of feature elements in the one feature vector", which is not taught or disclosed by RFT. The rejection of claims 19 and 20 is stated (p. 14) to be on the same basis as the rejection of claim 2.

Neither reference provides any teaching of "generating a new plurality of query vectors based at least in part on the feedback; generating a weighting of feature elements based at least in part on the feedback; and selecting a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors", as recited in claim 2. RFT teaches use of a fixed (and apparently predetermined) set of feature vectors f_i, together with a set of weights that are the sole representation of feedback. MR teaches selection of a new query point q and does not teach generation of weighting elements based on feedback.

As a result, neither reference provides any teaching of "using a matrix in determining the distance between one of the new plurality of query vectors and one of the plurality of feature vectors", as recited in claim 2.

As noted in the Office Action (p. 12), RFT is silent with respect to selection of a matrix. RFT also fails to provide any criteria for such selection. The Office Action indicates that motivation to take the teachings of MR regarding matrix selection would be "to avoid the problem of a singular and non-invertible covariance matrix, as disclosed by MR."

However, RFT provides experimental results (§4, Figs. 3 and 4). The ideas disclosed by RFT do not encounter any such problem or issue. Such is *non sequitur* to anything contained in or disclosed by RFT. If such were a problem with the methods taught by RFT, RFT would have adopted techniques to address such. The fact that RFT didn't develop and adopt such techniques shows that this problem and such motivation are absent for the techniques disclosed by RFT.

The Office Action further states (p. 11) that further motivation lies in MR's building off of the MARS system and that such is explicitly referenced in RFT. Such does not comprise motivation.

MR mentions the MARS system as "Related Work" (section 2), stating that such is a query point movement system (section 2.1), which "directly applied the Rocchio's formula" and that such also proposes re-weighting (section 2.2). MR explicitly states (bottom, left side of p. 220) that their approach "does not use ad-hoc heuristics (such as β and γ in the Rocchio's formula". MR also explicitly states (Abstract; section 2.2; section 6)that the approach set forth by MR offers significant advantages that no other system can provide when compared to other systems.

MR explicitly states (p. 220) that the technique proposed by MR includes the query refinement technique of MARS as a special case but presents significant advantages (labeled (a) through (c)) relative to prior techniques. As such, MR is aware of the MARS project and certainly does not provide motivation to combine the teachings of RFT with those of MR.

Both references use a number of terms and labels in common - e.g., "vector", "database" etc. In fact, both references are written in *the same language.*

None of these facts are remarkable or constitute a basis for motivation to combine teachings or to modify teachings.

Additionally, claim 2 recites "using a matrix in determining the distance between one of the new plurality of query vectors and <u>one</u> of the plurality of feature vectors". In other words, a hierarchical approach is taken to determining how closely two images match: first individual distances between the feature vectors and the query vectors are determined and evaluated, and then these individual distances are combined.

RFT does not describe such an hierarchical process. RFT describes an approach whereby an object's similarity to a query object is evaluated (step 4), the representation's similarity values are combined into a feature's similarity value (step 5) and these similarities are then combined (step 6) to provide an overall similarity. This overall similarity is then employed to evaluate rank ordering (step 7).

In contrast to Applicant's claims, MR describes a process that also is not hierarchical - as shown by Calc. 4, which seeks to minimize sums over all N of the samples, of (Calc. 3) sums over all of the query vector elements and feature vector elements. There is no guidance contained in the references to show how to adapt the teachings of RFT to arrive at the hierarchical process described by claim 2, or of how to fold in selected bits and pieces of MR into the framework of RFT to somehow attempt to arrive at the subject matter recited in claim 2.

MR uses a matrix M to describe a generalized distance (see section 3.2). RFT does not describe any matrix with respect to steps (1) through (10). As a result, there is no motivation anywhere in RFT to import a matrix from any

reference to attempt to arrive at Applicants' claimed subject matter. As such, the proposed combination fails to provide the subject matter recited in any of claims 2 or 19.

Claim 3 recites "One or more computer readable media as recited in claim 2, wherein the dynamically selecting comprises using a diagonal matrix if the number of images in the set of potentially relevant images for which relevance feedback was input is less than the number of feature elements in the one feature vector, and otherwise using a full matrix", which is not taught, disclosed, suggested or motivated by the cited references, alone or in any proper combination.

The Office Action states (pp. 12, 13) that MR, as added to RFT, teaches the dynamically selecting with respect to claim 3 (p. 12) and that (p. 14) claims 21 and 22 are rejected on the same basis as claim 3. The discussion of application of MR and RFT to attempt to arrive at the subject matter of claim 3 relies on the rejection of claims 14 and 15. As noted above with respect to claims 14 and 15, RFT fails to provide any basis for discrimination between use of a full matrix and use of a diagonal matrix. Further, the Office Action is void of any discussion of how or why the teachings of MR might be combined with those of RFT. Clarification is requested. As such, the proposed combination fails to provide the subject matter recited in any of claim 3 or claims 21 and 22.

Claim 4 recites "One or more computer readable media as recited in claim 2, wherein the dynamically selecting comprises: if the number of images in the set of potentially relevant images for which relevance feedback was input is not less than the number of feature elements in the one feature vector, then using one

matrix that transforms the query vector and the one feature vector to a higher-level feature space and then using another matrix that assigns a weight to each element of the transformed query vector and the transformed feature vector; and if the number of images in the set of potentially relevant images is less than the number of feature elements in the one feature vector, then using a matrix that assigns a weight to each element of the query vector and the one feature vector", while claim 23 recites "A method comprising: generating a query vector corresponding to a feature of one image; identifying a feature vector corresponding to the feature of another image; identifying a number of training samples for which relevance feedback has been received; if the number of training samples either equals or exceeds a threshold amount, then determining a distance between the query vector and the feature vector including transforming the query vector and the feature vector to a higher-level feature space and then assigning a weight to each element of the transformed query vector and the transformed feature vector; and if the number of training samples does not exceed the threshold amount, then determining the distance between the query vector and the feature vector including assigning a weight to each element of the query vector and the feature vector" and claim 30 recites "A system comprising: a query vector generator to generate a query vector corresponding to a feature of one image; a comparator, coupled to the query vector generator, to, identify a feature vector corresponding to the feature of another image, identify a number of training samples for which relevance feedback has been received, if the number of training samples either equals or exceeds a threshold amount, then to determine a distance between the query vector and the feature vector including transforming the query vector and the feature

vector to a higher-level feature space and then assigning a weight to each element of the transformed query vector and the transformed feature vector, and if the number of training samples does not exceed the threshold amount, then to determine the distance between the query vector and the feature vector including assigning a weight to each element of the query vector and the feature vector", which is not taught, disclosed, suggested or motivated by RFT or MR, alone or in any proper combination.

The Office Action states (pp. 12, 13) that MR, as added to RFT, teaches the dynamically selecting of claim 4 (p. 13) and that (p. 14) claims 23, 24, 29 and 30 stand rejected on the same basis as claim 4.

The discussion relative to claim 4 of application of MR and RFT to attempt to arrive at the claimed subject matter focuses on section 3.3 of MR. However, that portion of MR discusses minimization of a distance function as shown in Calc. 4. In each case, whatever transformation of query vectors takes place involves the same dimensions of feature space and the same weighting procedures.

Additionally, MR describes use of one matrix M under one set of condition, and another matrix M otherwise. There is no description in MR, RFT or the Office Action of "transforming the query vector and the feature vector to a higher-level feature space", followed by "then assigning a weight to each element of the transformed query vector and the transformed feature vector", as recited in claims 4, 23 and 30.

Further, the Office Action is void of any discussion of how or why the teachings of MR might be combined with those of RFT. Clarification is requested.

MR, with or without RFT, changes the choice of matrix M, but does not provide any description of transformation and weighting of query and feature vectors and thus cannot possibly provide criteria for when such transformation should be applied, as recited in claims 4, 23 and 30. As such, the proposed combination fails to provide the subject matter recited in any of claim 4 or claims 23, 24, 29 and 30.

Additionally, there is no guidance in the references as to how to adapt the teachings of RFT to arrive at the claimed subject matter or of how to fold in selected bits and pieces of MR into the framework of RFT to somehow attempt to arrive at the subject matter recited in claim 4, 23 or 30.

Claim 5 recites "One or more computer readable media as recited in claim 2, wherein X represents an image matrix that is generated by stacking N feature vectors, each of length K, corresponding to the set of potentially relevant images for which relevance feedback was received and resulting in an (N x K) matrix, C represents a weighted covariance matrix of X, det(C) represents the matrix determinant of C, and the matrix comprises a full matrix (W^*) that is generated as follows: $W^* = (\det(C))^{\frac{1}{K}} C^{-1}$, while claim 7 recites "One or more computer readable media as recited in claim 1, wherein N represents the number of images in the set of potentially relevant images for which relevance feedback has been received, π_n represents the relevance of image n in the set of images, $\vec{\pi}^T$ represents a transposition of a vector generated by concatenating the individual π_n values, and X represents an image matrix that is generated by stacking N training vectors corresponding to the set of potentially relevant images into a matrix , and wherein each new query vector ($\vec{q}$) of the new plurality of query vectors is

generated as follows: $\vec{q} = \frac{\vec{\pi}^{T} X}{\sum_{n=1}^{N} \pi_n}$" and claim 55 recites "One or more computer readable media including a computer program that is executable by a processor to cause the processor to perform acts of: receiving user feedback regarding the relevance of each image of a set of images, the user feedback forming a range including at least Highly Relevant, Relevant, No Opinion, Irrelevant, and Highly Irrelevant; wherein N represents the number of images in the set of images for which user feedback has been received, π_n represents the relevance of image n in the set of images, $\vec{\pi}^{T}$ represents a transposition of a vector generated by concatenating the individual π_n values, and X represents an image matrix that is generated by stacking N training vectors corresponding to the set of images into a matrix; and generating a query vector ($\vec{q}$) corresponding to one of a plurality of features as follows: $\vec{q} = \frac{\vec{\pi}^{T} X}{\sum_{n=1}^{N} \pi_n}$", which is not taught, disclosed, suggested or motivated by the cited references. Claim 55 is stated (p. 15) to be rejected on the same basis as claim 7.

As noted above with reference to claim 46, MR does not teach or disclose stacking N feature vectors corresponding to the set of potentially relevant images for which relevance feedback was received, or any (N x K) matrix. MR teaches (with respect to theorem 1) that a query vector = X^T(goodness values)/(sum of goodness values), where X represents the entire data point matrix (see Table I). This differs from the recitation of claims 5, 7 or 55, which provide that concatenating relevance values times an image matrix formed by stacking N training vectors provides an image matrix X, or that "C represents a weighted

covariance matrix of X, $\det(C)$ represents the matrix determinant of C, and the matrix comprises a full matrix (W^*) that is generated as follows: $W^* = (\det(C))^{\frac{1}{K}} C^{-1}$", as recited in claim 5, or that "each new query vector ($\vec{q}$) of the new plurality of query vectors is generated as follows: $\vec{q} = \frac{\vec{\pi}^T X}{\sum_{n=1}^{N} \pi_n}$", as recited in claims 7 and 55.

The Office Action offers (p. 13) Theorem 2 of RFT as providing the subject matter of claim 5. Claim 5 refers to a full matrix. Theorem 2 is explicitly devoted to a diagonal matrix of variances σ_j^2.

The Office Action is void of any discussion of how or why the teachings of MR might be combined with those of RFT. Clarification is requested. As such, the proposed combination fails to provide the subject matter recited in any of claims 5, 7 or 55.

Further, there is no teaching or disclosure in MR of searching images, or of "receiving feedback regarding the relevance of each image of a set of images", as recited in claims 7 and 55. MR is silent with respect to searching images.

Applicant notes the requirements of MPEP §2143, entitled "Basic Requirements of a Prima Facie Case of Obviousness" (see also MPEP §706.02(j), entitled "Contents of a 35 U.S.C. 103 Rejection."). MPEP §2143 states that "To establish a prima facie case of obviousness, three basic criteria must be met. First, there must be some suggestion or motivation, either in the references themselves or in the knowledge generally available to one of ordinary skill in the art, to modify the reference or to combine reference teachings."

Inasmuch as the references fail to teach or disclose the elements recited in the claims, the references cannot provide motivation to modify their teachings to

arrive at the invention as claimed, and the Examiner has identified no such teaching or disclosure in the references. As a result, the first prong of the test cannot be met.

MPEP §2143 further states that "Second, there must be a reasonable expectation of success. Finally, the prior art reference (or references when combined) must teach or suggest all the claim limitations."

Inasmuch as the references fail to provide all of the features recited in Applicant's claims, the third prong of the test is not met. For example, as noted above, the references are silent with respect to computer readable media, as recited in claims 2-7, 19-22, 29 and 53-56. As a result, there cannot be a reasonable expectation of success. As such, the second prong of the test cannot be met.

MPEP §2143 additionally states that "The teaching or suggestion to make the claimed combination and the reasonable expectation of success must both be found in the prior art, not in applicant's disclosure. *In re Vaeck*, 947 F.2d 488, 20 USPQ2d 1438 (Fed. Cir. 1991)." This criterion cannot be met because the references fail to teach or disclose the elements recited in the claims. Accordingly, the unpatentability rejections based on RFT, with or without the teachings of MR, fail all of the criteria for establishing a prima facie case of obviousness as set forth in the MPEP.

Moreover, no evidence has been provided as to why it would be obvious to modify and/or combine the teachings of these references. Evidence of a suggestion to combine may flow from the prior art references themselves, from the knowledge of one skilled in the art, or from the nature of the problem to be solved. However, this range of sources does not diminish the requirement for actual

evidence. Further, the showing must be clear and particular. See *In re Dembiczak*, 175 F.3d 994, 998 (Fed. Cir. 1999).

For at least these reasons, Applicant respectfully requests that the §103 rejections be withdrawn, and that Applicant's claims 1-30, 32-38, 40-44 and 46-56 be allowed.

Conclusion

Claims 1-30, 32-38, 40-44 and 46-66 are in condition for allowance. Applicant respectfully requests reconsideration and issuance of the subject application. Should any matter in this case remain unresolved, the undersigned attorney respectfully requests a telephone conference with the Examiner to resolve any such outstanding matter.

Respectfully Submitted,

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